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GLCM-BASED FINGERPRINT RECOGNITION ALGORITHM

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Abstract

An efficient and reliable fingerprint recognition system is the fundamental need of contemporary living. Beside forensic use, it has been deployed in a large number of commercial applications recently. In this paper, a new method for fingerprint recognition is introduced. The Core point is found initially using Poincare Index method. The dominant fingerprint region around the core point is selected and enhanced using the Diffusion Coherence Technique. The Gray level Co-occurrence Matrix (GLCM) is then applied to find out the fingerprint most significant statistical descriptors. Finally the K-Nearest Neighbor (KNN) Classifier is adopted for the recognition of unknown fingerprint images. The proposed algorithm is tested on images from FVC 2002 public domain database DB1. The experimental results demonstrate the improved performance of the algorithm.

Keywords: Fingerprint Recognition; Coherence Diffusion; GLCM;KNN Classifier

1 Introduction

Reliable and an authentic personnel identification is essential in contemporary life and is required by a large number of systems, deployed all over the world, to determine the identity of the individual asking to use their services and to insure that the provided services or access to information are used only by genuine users [1]. Access to buildings requiring an extreme security, an electronic commerce system through the internet, computer systems, laptops, cellular phones and automated teller machines (ATMs) are few examples of such systems [2].Without a reliable means of recognition, these systems can easily be deceived by imposters. In the future ubiquitous society, these applications will expand and the protection of personal information will become more important. The most reliable means of identifying an individual is using his/her intrinsic physical or behavioral characteristics called biometrics such as face, voice, hand writing, fingerprint, iris, gait etc[3]. Based on these traits, the system can recognizes the person based on "who" the person is and does not rely on "what a person is carrying, e.g. an ID card" or "what a person knows, e.g. Password"[4]. It transfers the access key from being on you to you and replaces the worries associated with the use of keys, personal identification numbers (PINs) and access cards with a keyless access, added security and a piece of mind [5].

Among all biometric recognition schemes, fingerprint is one of the most widely studied and used form of recognition [2], with its history dates back to 1800 century [6]. It is the cheapest, fastest, most convenient and highly reliable way to identify an individual. Initially fingerprint has been used in forensic applications only to identify criminals, but now it is used for a variety of government and commercial applications all over the world because of their high immutability and individuality. Few such government applications include Border control, National ID card, Driver License and Social Security, where as ATMs, Credit cards, Personal Computers, Laptops, Banking Electronic Transactions, computer Networks, Time Attendance, Cellular Mobile Phones and PDAs are few examples of commercial applications [8].

Fingerprint recognition can be achieved using the following three approaches [2].

- Fingerprint recognition using minutiae details.
- Fingerprint recognition using image correlation
- Fingerprint recognition using texture Analysis

The minutiae based matching involve the extraction of minutiae sets from the template and the query images, establishing the alignment between the two minutiae sets and the calculation of match score based on the number of correspondences between the two minutiae sets. In automatic fingerprint matching only two types of minutiae (ridge ending and bifurcation) have been used due to its stable nature and reliable extraction. The important information of minutiae includes its type, location and direction. A greater number of corresponding minutiae pairs in query image and template produce a higher matching score. Although this type of

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matching produce better results for full and high contrast images, it gives poor results for low quality images and those with partial overlap area like in latent fingerprints which are obtained from crime scenes and which do not have a sufficient number of minutiae to identify. In low quality images, this method may produce false (spurious) minutiae and miss some genuine minutiae. Hence the system performance deteriorates eventually in such situations.

In the correlation-based matching, the query and the template images are superimposed and the image correlation is carried out between the corresponding pixels for different alignments. This method has been found to be computationally expensive, in addition to its sensitivity to non linear distortion, which makes two impressions of the same fingerprint different from one another.

The third type of matching algorithm is useful for low quality images where the minutiae details cannot be extracted reliably. In this type of matching, the texture information of the image is used to find the similarity and differences between the two images. This method provides better results for low quality images than the minutia based and correlation based methods [9-10].

In this paper we propose a new approach of fingerprint recognition using GLCM-based statistical descriptors as a texture feature set. The core point is initially found using the Poincare Index method. The surrounding region of core point, which contains the most significant features of fingerprint, is selected for texture extraction. This region is then enhanced using the Diffusion Coherence technique which gives good results for high curvature regions. The KNN Classifier is finally adopted to carry out the recognition process with different combinations of fingerprint images. The proposed approach is tested on images of FVC 2002 public domain Database DB1.

The remainder of the paper is organized as follows. In section 2, we briefly review the theory of Poincare Index, Diffusion Coherence, GLCM and KNN algorithm used in the Proposed Recognition Algorithm. In section 3, the Proposed Algorithm is described in detail. Section 4 presents the results of our experiments. Section 5 summarizes the paper with a brief conclusion.

2 Related work

2.1 Poincare index

The core point in the fingerprint is the point of maximum ridge line curvature as shown in Figure 1. Around this point the ridge orientation changes very quickly and has been used both for fingerprint classification and matching algorithms. To determine the core point location, an effective and practical method of Poincare index was proposed by [11], which is summarized as given below [12].

1) Divide the input image $I(m,n)$ into non-overlapping blocks with size N x N, compute the gradients $\partial x(m,n)$ and $\partial y(m,n)$ at the center of the block and estimate the local orientation using the equations (1), (2) and (3).

$$O_x(m,n) = \sum_{n=0}^{N-1}\sum_{m=0}^{N-1} 2\partial_x(m,n)\partial_y(m,n) \qquad (1)$$

$$O_y(m,n) = \sum_{n=0}^{N-1}\sum_{m=0}^{N-1} (\partial_x{}^2(m,n) - \partial_y{}^2(m,n)) \qquad (2)$$

$$\theta(m,n) = \frac{1}{2}\tan^{-1}\left(\frac{O_y(m,n)}{O_x(m,n)}\right) \qquad (3)$$

Where $\theta(m,n)$ is the least square estimate of the local block ridge orientation centered at pixel (m , n).

2) Smooth the orientation field by averaging of gradient vectors and using a low pass filtering by first converting the orientation image into a continuous vector field as proposed by M. Bazen and H. Gerez [13]

3) For each pixel, compute Poincare index, PC (m, n) using (4), (5) and (6) as given below.

$$PC(m,n) = \frac{1}{2\pi}\sum_{k=0}^{N_p-1}\Delta(k) \qquad (4)$$

The core point should yield the Poincare index between 0.45-0.51.If there are more than one block with this value, the average calculation is then applied accordingly [13].

$$\Delta(k) = \begin{cases} \delta(k) & \text{if } \delta(k) < \pi/2 \\ \pi + \delta(k) & \text{if } \delta(k) < -\pi/2 \\ \pi - \delta(k) & \text{otherwise} \end{cases} \qquad (5)$$

$$\delta(k) = \varepsilon(x(k+1)_{\bmod Np}, y(k+1)_{\bmod Np}) - \varepsilon(x_k, y_k) \qquad (6)$$

2.2 Non-linear coherence diffusion

Coherence-enhancing filtering is useful for filtering relatively thin and linear structures. It is a specific technique within the general classification of diffusion filtering. Diffusion filtering, which models the diffusion process, is an iterative approach of spatial filtering in which image intensities in a local neighborhood are utilized to compute new intensity values. In linear diffusion the filter coefficients remain constant throughout the image, while nonlinear diffusion means the filter coefficients change in response to differential structures within the image. Coherence-enhancing filtering is a regularized nonlinear diffusion that attempts to smooth the image in the direction of nearby pixels with similar intensity values.

Mathematically, the diffusion process in an image I(m,n) can be expressed as the second-order PDE shown by (7).

$$\partial_t I = \text{div}\ (D \cdot \nabla I) \tag{7}$$

Where *div* shows the divergence operator; *D is the* diffusion tensor and ∇I is the Image Gradient. In Nonlinear diffusion filtering, the image is smoothed out prior to computing the gradient and can be described by (8).

$$\partial_t I = \text{div}\ (\mathrm{D}|\ \nabla \mathrm{I}_\delta \,|\, \nabla \mathrm{I}_\delta) \tag{8}$$

Coherence-enhancing anisotropic diffusion is an extension of edge-enhancing anisotropic diffusion that is specifically tailored to enhance line-like image structures by integrating orientation information. The diffusivity tensor for this is given by equation (9). In this diffusivity tensor, K_ρ is a Gaussian kernel of standard deviation 'ρ', which is convolved with each individual component of the $\nabla \mathrm{I}_\delta (\nabla \mathrm{I}_\delta)^T$ matrix [14]. The proposed algorithm uses the coherence-enhancing anisotropic diffusion filter proposed by Weickert [15].

$$D(\nabla Is) = D(\ \mathrm{K}_\rho \otimes \nabla \mathrm{I}_\delta (\nabla \mathrm{I}_\delta)^T) \tag{9}$$

2.3 Gray Level Co-Occurrence Matrix (GLCM)

Gray level co-occurrence matrix (GLCM) was first proposed by Haralick [16] and is one of the most well-know and widely used texture feature extraction method. It estimates the second-order statistics properties of the images and provides valuable information about the relative position of the neighboring pixels in an image. Because of its effectiveness in texture analysis, this method is very effective in recognition applications [17]. It is essentially a two-dimensional histogram in which every element (m, n) is the frequency of event *m* co-occurs with event n. A co-occurrence matrix is specified by the relative frequencies *P(m, n , d, θ)* in which two pixels are separated by distance *d and* occur in a direction specified by the angle θ, one with gray level m and the other with gray level n. A co occurrence matrix is therefore a function of grayscales values (*m,* n), separation distance d between these pixels and angle θ of computation. For an Image I of size N×N, the co occurrence matrix can be described as given by (17) [18].

$$G(m,n) = \sum_{x=1}^{N}\sum_{y=1}^{N} \begin{cases} 1, & \text{if } \mathrm{I(x,y) = m\ \&\ I(x{+}\Delta x, y{+}\Delta y) = n} \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

Where Δ_x and Δ_y are the offset and specify the distance between the pixel-of-interest and its neighborer.

Multiple GLCMs are computed for different orientations of θ at 0°, 45°, 90°, and 135° which can describe soundly the spatial relationship between neighboring pixels and can result in reliable texture features of fingerprint images. After the GLCMs are computed for every image, then it is used to calculate the statistical descriptors which uniquely describe the fingerprint images. The statistical descriptors used in the proposed algorithm are given in Section 3 in detail.

2.4 K-Nearest Neighbor (KNN) Algorithm

KNN algorithm is a traditional pattern recognition method based on statistics. It is analytically tractable and has very simple implementation. It uses local information and can yield highly adaptive behavior.

The KNN Classifier is trained with a set of images selected as the training set and the remaining images consist of the testing set [19].

The classifier finds the k points in the training set that are the closest to point x using the minimum Euclidean distance or city block (sum of absolute differences) as a distance metric and assigns x the label, shared by the majority of this k nearest neighbors. Distance measurement is mostly carried out in the feature space where the feature vectors of training samples are preserved. The proposed algorithm has been evaluated with different values of k and distance metrics.

3 Proposed algorithm

The fingerprint verification algorithm used in [12] involves the computations of four GLCM-based descriptors only with separation distance of four pixels. Whereas the proposed algorithm compute seven statistical descriptors with GLCM separation distance of 1, 2 and 3 pixels. The method used for enhancement in our algorithm preserve the ridges high curvature around the core point and hence provides improved enhancement of the low quality images. The algorithm is described in detail as follows.

Step 1: Determine the core point of the image using the Poincare index method, as explained in the Section 2. "Fig.1," shows the results of applying the method to images from FVC 2002 databases.

Step 2: Select the high-curvature region of dimensions 100×100 pixels surrounding the core point location found in step 1."Fig. 2," shows this selected region of three images.

Step 3: Apply the Diffusion Coherence method of image enhancement, as explained in Section 2, to the selected region determined in step 2."Fig. 3," shows the enhanced images.

Step 4: Find the Gray Co occurrence Matrices (GLCM) with distances of 1, 2 and 3 pixels in the four orientations of 0, 45, 90 and 135 degrees each for the images obtained in step 3.

Step 5: Use the GLCMs, obtained in step 4, to calculate the following descriptors for feature vector to be used in the recognition algorithm.

1) Contrast

$$=\sum_m \sum_n \left[(m-n)^2 \times G(m,n,d,\theta) \right]$$

2) Dissimilarity

$$= \sum_m \sum_n \left[(m-n) \times G(m,n,d,\theta \right]$$

3) Energy

$$= \sum_m \sum_n \left[G^2 (m,n,d,\theta) \right]$$

4) Entropy =

$$\sum_m \sum_n \left[G(m,n,d,\theta) \times \log_{10} G(m,n,d,\theta) \right]$$

5) Homogeneity

$$=\sum_m \sum_n \left[G(m,n,d,\theta) \Big/ 1+|m-n| \right]$$

6) Maximum Probability

$$=\text{Max}_{\text{m,n}} \left(\sum_m \sum_n \left[G(m,n,d,\theta) \right] \right)$$

7) Variance

$$= \sum_m \sum_n \left[(m-Avg)^2 \times G(m,n,d,\theta) \right]$$

Figure 1 Images from FVC 2002 Database DB1 with Core Point location highlighted as green point

Figure 2 Selected Image Region around the core point for features extraction

Figure 3 Diffusion Coherence Enhancement of the Image selected region.

Step 6: After feature set of 28 values (seven descriptors for four orientations) is obtained for every image, then it is normalized and employed to train the knn classifier which is subsequently used for recognition task.

4 Experimental results

The proposed recognition algorithm is applied on the FVC 2002 public domain Database DB1, which contains 80 fingerprint images from 10 participants with 8 images per finger. These images were divided into training and testing sets. Six images of each individual were chosen for training process of knn classifier and the remaining two images were selected for testing purposes. The experiments have been performed for different combinations of training and testing sets. The statistical descriptors mentioned in Section III are obtained from GLCMs with different separation distances between pixels. For every fingerprint image we get a feature set of twenty eight values comprising of seven statistical descriptors in four orientations 0^0, 45^0, 90^0 and 135^0 of GLCMs. These feature sets are normalized and are then used to train and test knn classifier with different values of k nearest neighbors. The experiments are repeated by changing the distance metric of knn classifier to Euclidian distance and city block distance.

Table 1 shows the results of our experiments. It is obvious from these results that the proposed algorithm of fingerprint recognition performs well, gives good recognition accuracy and can be applied to low quality images. It has been found that the combination of GLCM separation distance of 2 pixels, with 2 nearest neighbors in knn classifier and an Euclidian distance as a distance metric give the highest recognition accuracy. Also it has been observed that the recognition rate is always higher for Euclidian distance than the city block, which is the sum of absolute differences between nearest neighbors.

5 Conclusions

In this paper an algorithm for fingerprint recognition has been proposed. Seven significant statistical descriptors have been calculated using the GLCM with different pixels separation distances between pixels in four orientations. These descriptors are then used to build a feature set which uniquely describe the selected enhanced fingerprint image.region surrounding the core point. The core point is detected using the Poincare Index method and the enhancement is achieved with Diffusion Coherence Technique. The experimental results show that the Proposed Algorithm achieve good recognition accuracy for different combinations of GLCMs pixels separation distances, number of nearest neighbors and distance metrics used in knn classifier and can be used for identification of fingerprints with low quality and noisy backgrounds in a database with limited number of images.

Table 1 Experimental results of the proposed recognition algorithm

GLCM Pixels Separation Distance	No. of Nearest Neighbors used in KNN	Distance Metric used in KNN	No. of Correctly Recognized Images	Recognition Accuracy (%)
1	1	Euclidian Distance	75	93.75
		City Block	73	91.25
	2	Euclidian Distance	76	95
		City Block	73	91.25
	3	Euclidian Distance	75	93.75
		City Block	72	90
2	1	Euclidian Distance	78	97.5
		City Block	76	95
	2	Euclidian Distance	79	98.75
		City Block	77	96.25
	3	Euclidian Distance	76	95
		City Block	75	93.75
3	1	Euclidian Distance	74	92.5
		City Block	72	90
	2	Euclidian Distance	73	91.25
		City Block	69	86.25
	3	Euclidian Distance	71	88.75
		City Block	69	86.25

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